# Regulatory airport classification in the US: the role of international markets.

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# REGULATORY AIRPORT CLASSIFICATION IN THE US: THE ROLE OF INTERNATIONAL MARKETS

## 1. INTRODUCTION

The US Federal Aviation Administration (FAA) provides grants to airports for capital developments under the Airport Improvement Program (AIP). The AIP is one of five major sources of airport capital development funding. The other sources are tax-exempt bonds, passenger facility charges (PFC), state and local grants, and airport operating revenue. Different airports use different combinations of these sources depending on the individual airport's financial situation and the type of project being considered. Small airports are more dependent on AIP grants than large or medium sized airports. The larger airports, whose projects tend to be much more costly, are more likely to participate in the tax-exempt bond market or finance capital development projects with a PFC (Kirk, 2007). Hence, although the AIP may not be the main source of finance for major airports, it is still an important source of capital for improvements related to airport safety, capacity, security and the environment. In 2014, $586.2 million in AIP funds were allocated to the 30 largest hubs in the US (approximately 18.2% of the nationwide grants).

The latest estimates for the AIP budget indicate a 19% decrease ($52.2 billion to $42.5 billion) for the period 2013-2017, with respect to the estimates provided two years earlier (FAA, 2012). While this drop can be linked to the waning effect of the economic stimulus legislation (DOT, 2013), the FAA has also been pressured to reduce its budget; the Department of Transportation (DOT) pointing at cost inefficiencies as the root of the problem (DOT, 2013:113). From the Agency's perspective, a debate on the future of the FAA's funding model has been proposed (Flightglobal, 2013).

Within a context of financial constraints, public spending should look for a higher efficiency and impact of the resources invested. In this regard, this paper develops a new US airport typology that can help optimise the AIP. The current statutory classification is defined in the National Plan of Integrated Airport Systems (NPIAS) report, which groups airports according to their size and role within the US network and it is mainly based on each airport's share of the total US passenger enplanements (Table 1).

**Table 1.**FAA's system of airport classification.

| ***Commercial Airport Type*** *At least 2,500 boardings* | ***Hub type*** *Percentage of US-wide annual passenger enplanements (739.3 million enplanements in 2013)* | ***Common name*** |
|---|---|---|
| Primary | **Large** 1% or more | Large Hub |
| | **Medium** At least 0.25%, but less than 1% | Medium Hub |
| | **Small** At least 0.05%, but less than 0.25% | Small Hub |
| | **Non-hub** More than 10,000 enplanements, but less than 0.05% | Non-hub Primary |
| Non-primary | **Non-hub** At least 2,500 and no more than 10,000 | Non-primary Commercial Service |

*Sources: Title 49 U.S.C., Section 40102; FAA passenger enplanement data.*

The annual AIP budget is split between "entitlements" and "discretionary" funds. Primary airports (see Table 1) are entitled to receive an annual apportionment of at least $1 million in AIP funds with the total amount determined by the number of enplaned passengers (FAA, 2012). Discretionary funds, on the other hand, are prioritized by the FAA using a National Priority System (NPS) formula that combines four factors (FAA, 2000): i) the airport size and role (based on the typology from Table 1), ii) the purpose of the project (e.g., increase capacity), iii) the physical component (e.g., runway), and iv) the type of work (e.g., extension). Numeric weightings associated with these factors reflect the FAA's strategic goals, which are currently oriented to enhancing safety and security, capacity, and environmental performance (FAA, 2012). With regard to the "airport size and role" factor, large and medium hubs receive the same weighting.

This airport typology plays a role in allocating both entitlements and discretionary funds, but one may argue that the FAA typology is too broad, especially for primary airports. The major changes in airline network structures after deregulation suggest that the role of primary airports is linked to their ability to support hub-and-spoke operations, which are typically achieved by consolidating originating and transfer passenger flows (Button, 2002; Doganis, 2010). In fact, the existence of these two dimensions of "hubbing" (traffic generation and connectivity) is acknowledged in the NPIAS report, but they are not explicitly incorporated in the method for hub classification. Since one of the main objectives of the AIP is to reduce congestion and delays, from a social perspective it seems reasonable that funding priority should be given to airports playing a central role in the network, not just because they process a significant proportion of US traffic but also because passengers are connecting through them to other destinations, which will also benefit from delay reductions at the hub. Hence, there is a potential to optimise the social benefits from AIP investments by changing the NPIAS airport classification to explicitly acknowledge the importance of hub connectivity along with the airport's potential for traffic generation.[1]

Previous papers have already addressed the limitations of the FAA's uni-dimensional method along the same lines (Rodríguez-Déniz et al., 2013), and proposed alternative approaches that take into account airport size, traffic generation and connectivity (Adikariwattage et al., 2012). However, these studies are biased by the lack of detailed data on international markets, which is not provided by the widely-used DOT traffic databases. This prevents a full characterisation of the hubbing activity at the largest airports, for which precise classification is most crucial.

Using the well-known Marketing Information Data Transfer (MIDT) database, comprising a large sampleof domestic and international marketsserved by US airports during the first quarter of 2013, this paper aims at providing a full picture on the pitfalls of the existing FAA method by assessing the impact of actual international connectivity in characterising the airports' hubbing profiles. A second objective is to provide an alternative set of unbiased criteria for hub classification within the context of the NPIAS, for which hierarchical clustering techniques will be employed.

The paper is structured as follows: Section 2 reviews the history of the Airport Improvement Program, previous literature on regulatory airport classification and the measurement of connectivity. Section 3 describes the data and methodology, from the indicators of hubbing activity to the hierarchical clustering techniques. Section 4 presents the results, discusses the importance of appropriately measuring hubbing activity in international markets, and provides alternative classification criteria for US airports. Section 5 presents the conclusions.

## 2. BACKGROUND: THE AIP, AIRPORT CLASSIFICATIONS AND DEMAND-BASED CONNECTIVITY

[1] The proposed method places the emphasis on the concept of hubbing, which it is traditionally linked to the activity of full service network carriers (FSNC). However, the belief that low-cost carriers (LCCs) do not offer connecting services is not valid anymore. In fact, the largest US low-cost carrier (i.e., Southwest) offers connections between its flights and the growth limits of the LCC business model is forcing some of these carriers to consider hybrid strategies that include facilitating transfers (de Wit and Zuidberg, 2012). Therefore, the method presented in the paper avoids the traditional differentiation between FSNC and LCC and, instead, discriminates by the type of service,i.e., between traffic generation and connectivity.

### *2.1 The Airport Improvement Program (AIP): a bit of history*

Airport grant programmes have been present in the US since after World War II. The first programme was approved in 1946 by means of the Federal Airport Act and drew its funding directly from the US Treasury. Later, in 1970, the Airport and Airway Development Act created a more comprehensive scheme by the creation of the Planning Grant Program (PGP) and the Airport and Airway Trust Fund, which accumulated revenues from airlines, air freight and aviation fuel taxes. The 1982 Airport and Airway Improvement Act substituted the PGP by the Airport Improvement Program (AIP), which has been modified several times, the last by the FAA Modernization and Reform Act of 2012. The Airport and Airway Trust Fund remains the funding source of the AIP and is still supported by different aviation charges (FAA, 2014).

The current system has been a matter of debate in the industry and media (See, for example, USA Today (2009)). While larger airports have the capacity to attract more private funding and might not be heavily dependent on AIP funds, some critics consider that the AIP scheme is a way of subsidising airports with no commercial interest. Yet many other argue that the large US network of airports provides a wide range of social benefits such as access to air medical transport. In this regard, the public funding of US airports is a complex matter since the dependence on AIP to pay for capital needs depends not only on airport size, but also on political, commercial and market dynamics. On top of that, the evolution of the airport business, which is entering a new marketing oriented-era (Halpen and Graham, 2013), along with the view that airports are not just infrastructure providers anymore (Goedeking, 2010), may call for a full overhaul of the US public airport funding system.

### *2.2. Airport classifications and demand-based connectivity*

National and supranational authorities use airport classification for a wide variety of purposes (Table 2): these include slot allocation, delay management, allocation of public funding, assessment of competition, security regulations, or setting use charges within the national airport system. For all of these purposes, the idea of classifying airports according to the “role” they play within each network is always present and the relevance of connectivity in that respect becomes clear when the concepts of “hub” and “connecting” have been used by both the FAA and the European Commission (EC, 2005) to name their airport categories. In spite of that, total passenger traffic is by far the most popular criterion for airport classification, undoubtedly because of its transparency and simplicity. This aggregated approach ignores the fact that the split of passenger flows (originating and connecting) has a crucial impact on determining the airports' role within hub-and-spoke networks. To date, there has not been any assessment of connectivity in a regulatory airport classification setting. We aim to contribute in that aspect with a methodology that is more comprehensive while also remaining simple and transparent.

**Table 2.** Regulatory airport classifications

| *Authority* | *Country/Region* | *Purpose* | *Variables* | *Comments* |
|---|---|---|---|---|
| CEC (1993) | EU | Slot management | Slot capacity | 2 categories depending on potential congestion |
| CEC (1994) | EU | Network management | Passengers, Traffic mix, Aircraft movements, Cargo, Region | 3 categories: Community connecting points, regional connecting points, accessibility points (based on passenger traffic) |
| EC (2005) | EU | Airport competition | Passengers | 4 categories: <1, 1-5, 5-10, >10 million annual passengers |
| Eurocontrol (2008) | EU | Delay & Traffic statistics | Aircraft Movements | 8 categories (from 10,000 up to 500,000 annual ATMs) |
| Australian Government (2009) | Australia | Security | Airport role, Region, Aircraft type | 3 security categories: Major, Regulated screened, Regulated unscreened |
| FAA (2012) | US | Network management | Enplanements, based aircraft, aircraft movements | 7 categories: Large, medium & small hubs, nonhub primary, nonprimary commercial, reliever, and general aviation |
| Transport Canada (2012) | Canada | Network management | Passengers, Region | 2 categories: Nationally-significant airports and local/regional |
| IATA (2012) | International | Slot management | Slot capacity | 3 categories (levels) depending on potential congestion |
| AENA (2012) | Spain | Airport charges | Passengers | 4 categories: <0.5, 0.75-1.4, 2.4-5.6, 8.6-22.7, >35.3 million annual passengers (for 2011) |

Regarding the measurement of airport connectivity, we found a number of studies on the topic that adapt well-known indexes from other fields or propose ad-hoc ones. These studies are summarized in Table 3, where they are classified between supply-based and demand-based, since the approach is mainly dictated by their datasets. Supply-based studies focus on potential connectivity and employ data on flight schedules (typically from the Official Airline Guide - OAG) in order to either determine the maximum number of potential connections available to each arriving flight, or to assess the "centrality"of each airport based on the topology of the network and shortest-path length (or similar) criteria (Table 3).

For the purposes of this paper, we use a demand-based approach that focuses on actual connectivity. The few existing contributions concentrating on actual connectivity invariably use datasets that provide indication of full passenger itineraries (including intermediate stops) and hence allow for the desired disaggregation between originating and connecting traffic. Some of these studies have adapted the indicators of degree and betweenness centrality to the demand data for further exploration of the topological properties of airport networks (Jia and Jiang, 2012). Derudder et al. (2010), on the other hand, employed a more straightforward method and measured the number and proportion of connecting passengers at 20 airports from London, New York, Los Angeles, and San Francisco. Their results support our rationale as they show significant differences across large airports regarding their traffic split and role within airline networks.

**Table 3.** Airport connectivity/centrality studies

| *Author* | *Airport Sample* | *Region* | *Year* | *Source* | *Main Measures* |
|---|---|---|---|---|---|
| ***Supply Studies*** | | | | | |
| Bowen (2000) | 53 | World | 1979,97,98 | OAG | Degree, Shimbel Index |
| Burghouwt and Hakfoort (2001) | 467 | EU | 90,95,98 | OAG | Degree |
| Burghouwt and de Wit (2005) | 31 | EU | 90-99 | OAG | Weighted Indirect Connections |
| Guimerà et al. (2005) | 3,883 | World | 2000 | OAG | Degree, Betweenness |
| Danesi (2006) | 6 | EU | 04,05 | OAG | Danesi Connectivity |
| Reynolds-Feighan and McLay (2006) | 77 | World | 00,03,05 | OAG | Reynolds-Feyham and McLay Accessibility |
| Burghouwt (2007) | 570 | EU | 1999 | OAG | Weighted Indirect Connections |
| Guida and Maria (2007) | 42 | Italy | 05-06 | OAG | Betweenness |
| Budde et al. (2008) | All | World | 2007 | Lufthansa | Number of Connection Patterns |
| Malighetti et al. (2008) | 3,556 | World | 2006 | Innovata | Betweenness, Essential Betweenness |
| Matsumoto et al. (2008) | 13 | Asia- | 01,04,07 | OAG | Netscan Connectivity Units |
| Reggiani et al. (2008) | All | World | 2006 | OAG | Degree, Closeness, Betweenness |
| Paleari et al. (2010) | 1,268 | World | 2007 | Innovata | Betweenness |
| Berger (2011) | 3,496 | World | 2012 | OAG | Time-dependent transfer/connection centrality |
| Sapre and Parek (2011) | 84 | India | 2010 | ICAO | Degree, Closeness, Betweenness |
| Suau-Sanchez and Burghowt (2012) | 41 | Spain | 01,03,05,07 | OAG | Netscan Connectivity Units |
| Niesse and Grimme (2013) | 2,792 | World | 2012 | OAG | Avg. quickest travel time, Avg. quickest path |
| Redondi et al. (2013) | 379 | EU | 2011 | OAG | Accesibility Index |
| ***Demand Studies*** | | | | | |
| Derudder et al. (2010) | 20 | World | 2001 | MIDT | Absolute/Relative Hub Intensity |
| Wang et al. (2011) | 144 | China | 07-08 | CAAC | Degree, Closeness, Betweenness |
| Zeng et al. (2011) | 161 | China | 2010 | CAAC | Degree, Betweenness |
| Adikariwattage et al. (2012) | 209 | US | 2011 | DOT | Connecting passengers (domestic markets) |
| Jia and Jiang (2012) | 732 | US | 2010 | DOT | Degree, Betweenness |
| Rodríguez-Déniz (2012) | 400 | US | 2011 | DOT | Betweenness |
| Rodríguez-Déniz et al. (2013) | 400 | US | 93-12 | DOT | Degree, Betweenness, Flow Centrality |

Subsequent papers to Derudder et al. (2010) adapted these simple measures for their use in airport classification. Demand-based studies on US airport classification employ several datasets provided by the DOT in the Bureau of Transportation Statistics' website. The Airline Origin and Destination Survey (Database code: DB1B) is a 10% sample of all domestic tickets sold by US carriers with specific indication of the full itinerary for multi-sector journeys. This allows for the separation of originating and transfer passengersat the individual airports. Unfortunately, the DOT's data on international markets (T-100) is not as detailed and only origin and destination statistics are provided. Measuring international connectivity for individual airports is therefore not possible.

Using the DOT datasets, Adikariwattage et al. (2012)classified US airports using four variables: boarding gates, domestic origin-destination passengers, domestic transfers and international passengers (origin-destination and transfer combined). In order to justify the aggregated approach to international markets they argue that the impact of international transfers is likely to be negligible due to the low US-wide average proportion of international traffic (2%). This conclusion, however, is hardly applicable to the largest hubs that serve much higher proportions of international traffic, and for which the impact of international transfers is not negligible. As a consequence, their results are not particularly sensitive for the largest hubs, since all of them are grouped together in the same category (e.g., JFK, ATL, and CLT), despite showing radical differences in their hub profiles, as indicated in Section 4.

Rodríguez-Déniz et al. (2013) also employed DOT data to classify US airports according to traffic generation and connectivity. A new indicator of connectivity based on the concept of flow centrality is proposed and benchmarked against the traditional degree and betweenness centrality indices. A theoretical framework to measure both dimensions and link them to the FAA indicator was developed and applied to the domestic US airport network. They provided initial evidence on the shortcomings of the FAA method but, again, the analysis remains incomplete by the absence of international markets.

Against this background, the present paper builds its contribution on the advantages of the MIDT dataset, which provides detailed demand data on domestic and international markets served by US airports during the first quarter of 2013. To fully benefit from this data, however, there is also need to expand the basic framework fromRodríguez-Déniz et al. (2013)in orderto accommodate international traffic flows. Results provide the first demand-based assessment of the importance of international markets for hub characterisation, and help to determine the bias committed by previous studies. The analysis follows with a full picture on the pitfalls of the existing FAA method and the definition of an alternative set of criteria for hub classification, for which hierarchical clustering techniques established in the airport literature are employed.

## 3. DATA AND METHODOLOGY

### *3.1Measuring hubbing activity: connectivity and traffic generation*

In order to improve the FAA method, first we need to measure each airport's contribution to the US network in two different dimensions: traffic generation and connectivity. These are defined using the basic framework from Rodríguez-Déniz et al. (2013), who focused on domestic markets only.We expand its applicability to international and total markets. To that end, Figure 1shows how total network flows under different market definitions (i.e. domestic, international, and total markets) can be partitioned for each airport.

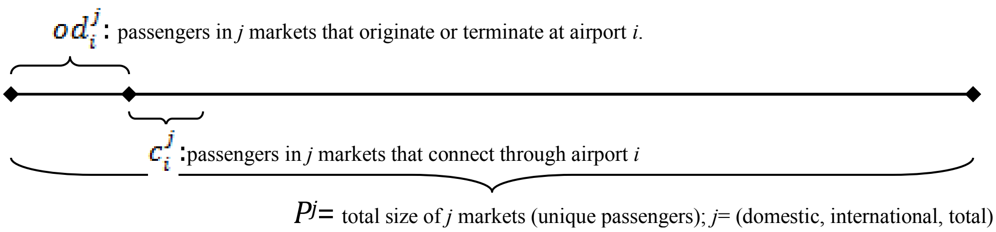


**Figure 1.**Partition of the total network flows in different markets with respect to the *i*-th airport

Using this notation, we can define two measures for each airport's contribution to the relevant network. The first one ($OD_i$) is calculated as the ratio between the passengers that originate or terminate at the *i-th* airport ($od_i$) and the size of the market ($P$). This quantifies the airport's importance as traffic generator. The second indicator ($C_i$) measures the airport's contribution to other *od* markets as a connecting gateway. It is calculated as the ratio between connecting passengers ($c_i$) and total network passengers that do not originate or terminate at the *i-th* airport[2] ($P - od_i$).Table 4 shows how these indicators are adapted to different market definitions, where$P^{dom}$, $P^{int}$, and $P^{tot}$ denote the total number of unique passengers in domestic, international, and total markets, respectively; $od_i^{dom}$ denotes domestic passengers that originate or terminate at airport $i$; $od_i^{US/int}$ denotes US↔international passengers that originate or terminate at airport $i$; and $c_i^{dom}, c_i^{US/int}$, and $c_i^{int/int}$denote the number of passengers that connect at airport $i$in domestic, US↔international, or international↔international routes, respectively.

[2] This measurement of connectivity is based on the concept of flow centrality from Freeman et al. (1991).In its original application to social networks, flow centrality was computed asthe total flow of information that passes through node*i*divided by the total flow between all pairs of nodes where *i*is neither a source of information nor its final destination. The extension of this concept to air transport is straightforward (Rodríguez-Déniz et al., 2013).

The size of the US domestic market ($P^{dom}$) is obtained by aggregating all *od*passengers at each airport ($od_i^{dom}$) and then dividing by 2 in order to remove duplicates.[3] This adjustment is not needed to compute the size of the international market ($P^{int}$), since international *od*passengers ($od_i^{US/int}$) are not duplicated as they either originate or terminate outside the US. Furthermore, connecting passengers that originate and terminate outside of the US ($c_i^{int/int}$) are also included in the size of the market since they are not counted as *od* elsewhere in our US-restricted network. The remaining ratios follow the same logic.

**Table 4.**Indicators of hubbing activity for different markets and equivalence with current FAA indicator

| | *Domestic markets* | *International markets* | *Total markets* |
|---|---|---|---|
| *Size of the market* | $P^{dom} = \frac{1}{2}\sum_i od_i^{dom}$ | $P^{int} = \sum_i od_i^{US/int} + c_i^{int/int}$ | $P^{tot} = P^{dom} + P^{int}$ |
| *Traffic generation* | $OD_i^{dom} = \frac{od_i^{dom}}{P^{dom}}$ | $OD_i^{int} = \frac{od_i^{US/int}}{P^{int}}$ | $OD_i^{tot} = \frac{od_i^{dom} + od_i^{US/int}}{P^{tot}}$ |
| *Connectivity* | $C_i^{dom} = \frac{c_i^{dom}}{P^{dom} - od_i^{dom}}$ | $C_i^{int} = \frac{c_i^{US/int} + c_i^{int/int}}{P^{int} - od_i^{int}}$ | $C_i^{tot} = \frac{c_i^{dom} + c_i^{US/int} + c_i^{int/int}}{P^{tot} - od_i^{dom} - od_i^{US/int}}$ |
| *Enplanements* | $E_i^{dom} = \frac{od_i^{dom}}{2} + c_i^{dom}$ <br> $E^{dom} = \sum_i E_i^{dom}$ | $E_i^{int} = \frac{od_i^{US/int}}{2} + c_i^{US/int} + c_i^{int/int}$ <br> $E^{int} = \sum_i E_i^{int}$ | $E_i^{tot} = E_i^{dom} + E_i^{int}$ <br> $E^{tot} = \sum_i E_i^{tot}$ |
| *FAA-equivalence (Total markets only)* | $FAA_i = \frac{E_i^{tot}}{E^{tot}} = OD_i^{tot}\frac{P^{tot}}{2E^{tot}} + C_i^{tot}\frac{P^{tot} - od_i^{dom} - od_i^{US/int}}{E^{tot}}$ | | |

Using this notation,it is also possible to establish an approximate analytical relationship between our indicators and the FAA method, which is based on each airport's share of enplanements over the US total ($E_i^{tot}/E^{tot}$). Domestic and international enplanements at each airport ($E_i^{dom}, E_i^{int}$) are defined by assuming symmetry between arriving and departing traffic flows and hence, *od*passengers are divided by 2 in order to remove the arrivals[4]. Additional enplanements by connecting passengers are also included in both markets.Bringing all these definitions into the FAA enplanement ratio allows us to arrive to the last equation of Table 4, which shows that the FAA is actually combining both hub dimensions into a single indicator. In Section 4, this formula will be used to map all combinations of $OD_i$ and $C_i$that yield the

[3] This is the same definition from Rodríguez-Déniz et al. (2013), though their notation is not as clear in that regard.
[4] This simplification is supported by the data that shows a very high degree of symmetry in both domestic and international *od* passenger flows.

same FAA value, with the intention to show the shortcomings of theiruni-dimensional method for hub classification.

### *3.2 Hierarchical clustering*

In order to produce an alternative airport typology, US airports will be classified according to $OD_i^{tot}$ and $C_i^{tot}$using agglomerative hierarchical clustering (AHC). The existing literature indicates that AHC has been the most popular choice to classify airports, yet a great degree of ad-hoc procedures are still used (Rodríguez-Déniz and Voltes-Dorta, 2014). The resulting hierarchical classification is typically presented in a tree-like diagram (i.e. dendrogram) that provides a much more informative structure than the flat clusters obtained from other partitioning methods, such as *k*-means.[5]Due to the insignificant values of both indicators at small airports, only those defined by the NPIAS as large, medium or small hubs (137 according to our data) will be included in this section. Starting from a matrix of pair-wise Euclidean distances between the airports, AHC performs a sequence of merge operations (governed by a predefined algorithm) that produce additional clusters at new levels of aggregation. We use the complete-linkage algorithm, which merges the nearest two clusters according to the farthest distance among their components, leading to more compact aggrupations. The resultingdendrogram can be truncated to reveal the actual clusters. The optimal truncation level is found using the pseudo-*F* coefficient based on the ratio of between-cluster variance to within-cluster variance (Calinski and Harabasz, 1974). The edges of the final clusters define the thresholds of our new airport categories.

### *3.3 Database*

Our MIDT dataset covers the first quarter of 2013 and provides information of more than 143 million passenger trips through 653 airports in the US network. Each record represents an airline booking and indicates the points of origin and destination, the connecting airport in one-stop itineraries[6], and the number of passengers. With regard to the markets included, Figure 2 describes the scope of our sample. Whereas the DOT provides full information on domestic markets only (origin and destination pairs located within the US), the MIDT dataset also includes itineraries in US↔international markets, where non-stop and transfer passengers

[5]General references to data clustering are Everitt et al. (2011) and Xu and Wunsch (2005).
[6] Our dataset does not have information on multi-stop bookings.

are observed, as well as the point of connection within the US for routes that originate and terminate in other countries.

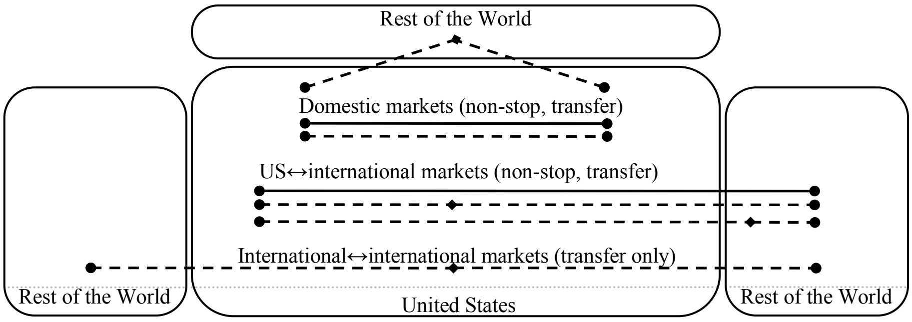


**Figure 2.**Scope of the MIDT dataset.
*Source: Own elaboration.*

Table 5 provides some summary statistics of the MIDT dataset. Note the significant contribution of international markets in both dimensions (15% in traffic generation and 28% in connectivity). This illustrates the bias incurred by previous studies in not characterising these markets properly.

**Table 5.**Summary statistics of the MIDT dataset.

| *2013 Q1* | | *Size of the market (Unique passengers)* | *%* | *Traffic Generation (od passengers)* | *%* | *Connectivity (Transfer passengers)* | *%* | *Enplanements* | *%* |
|---|---|---|---|---|---|---|---|---|---|
| ***Domestic markets*** | | 104,354,494 | 73% | 208,708,987 | 85% | 30,576,310 | 72% | 134,930,804 | 81% |
| ***International Markets*** | | 39,205,664 | 27% | 38,092,884 | 15% | 11,922,440 | 28% | 30,857,405 | 19% |
| | ***US/int*** | 38,092,884 | 26% | 38,092,884 | 15% | 10,809,660 | 25% | 29,744,625 | 18% |
| | ***int/int*** | 1,112,780 | 1% | 0 | 0% | 1,112,780 | 3% | 1,112,780 | 1% |
| ***Total markets*** | | 143,560,158 | 100% | 246,801,871 | 100% | 42,498,750 | 100% | 165,788,209 | 100% |

*Note: Enplanements column refers to actual enplanements, rather than enplanements predicted using the formulae from Table 4 Small discrepancies between actual and predicted values are related to the symmetry assumption.*

The original sources of information are Global Distribution Systems (GDSs) such as Travelport, Sabre, or Amadeus. According to ARG (2013), 44% of all bookings of major airlines[7] were done through GDSs in 2012. The proportion increases to 55% for network airlines, while low-cost carriers (LCCs), that prefer direct sales, only get 16% of their bookings via GDSs. This imbalance is an important limitation of the original data, due to the fact that LCCs tend to operate exclusively point-to-point flights, with little or no connectivity, as opposed to network carriers. In order to correct that, the provider of our data (OAG Traffic Analyser) adjusted the reservations data using mathematical algorithms based onfrequencies and supplied seats in each flight sector. The reliability of these adjustments is tested by

[7]This report uses a sample of 24 network/flag airlines and LCCs with annual revenues in excess US $1 billion.

comparing ourMIDT results for domestic markets with those obtained from the DOT database (see Section 4.1).

## 4. RESULTS AND DISCUSSION

### *4.1 Domestic markets*

While the limitations of a domestic-only analysis have already been noted, this subsection aims to assess the reliability of our MIDT sampleby comparing the domestic results with those obtained using the equivalentDOT dataset for the same time period. Figure 3 shows the distributions of domestic US passengers according to ticketing airline calculated using both datasets. It can be clearly seen that the distribution is almost identical in frequencies and ranking and that both network airlines and LCCs are fully represented.For domestic connecting markets, Figure 4 compares the hubbing indicators. A discrepancy can be found between the MIDT and DOT-based hub profiles, with the latter values being relatively higher in both dimensions. However, these differences are not expected to affect the classification of airports, since all of them preserve their relative position with respect to the other airports, and the distinct separations between the airport clusters are still observed. Thus,we conclude that our MIDT sample is at least as suitable for the purposes of this paper as the DOT dataset that has been used in previous studies.

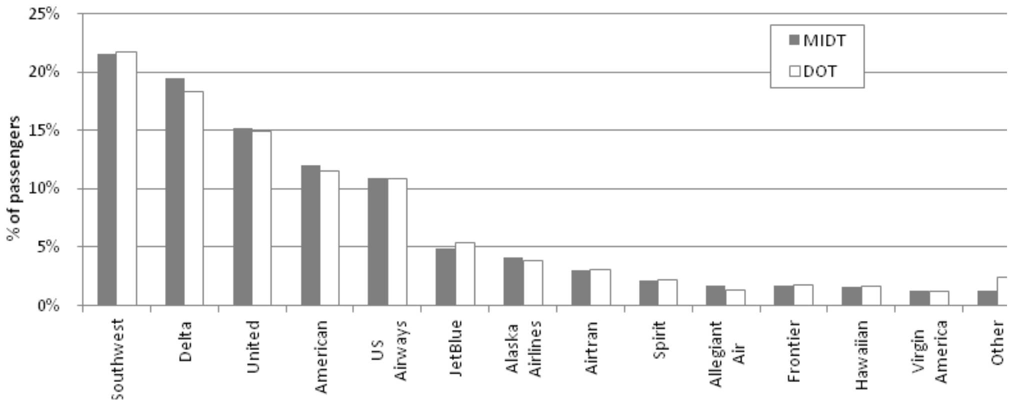


**Figure 3.** Distribution of US domestic passengers according to ticketing airline (2013 Q1)
*Source: Bureau of Transport Statistics and MIDT.*

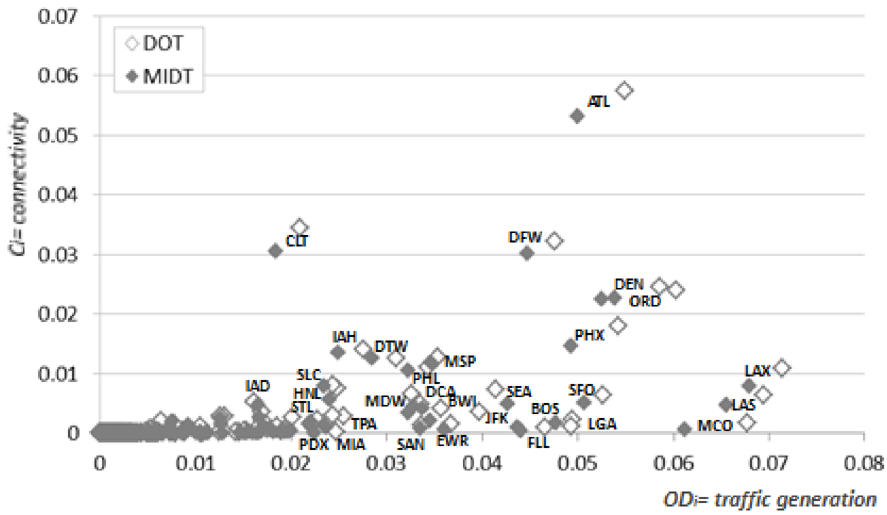


**Figure 4.**Hub characteristics for domestic markets: DOT vs. MIDT data (2013 Q1)
*Source: Own elaboration from the Bureau of Transport Statistics and MIDT.*

### *4.2International markets*

As expected, results for international markets indicate that the "hubbing" profiles for the largest airports vary widely (see Figure 5). On one end, Atlanta (ATL) can be clearly defined as an international waypoint, showing high levels of connectivity –almost 4% of international passengers in the US airport network that do not originate or terminate in ATL do connect through it– and limited traffic generation.[8] On the other end, New York's JFK serves a vast majority of *od* passengers(13% of international passengers in the US network originate or terminate at JFK) and a lower level of connectivity, similar in that aspect to its smaller competitor in Newark (EWR). This heterogeneity shows that international markets should be disaggregated when analysing airport "hubbing".

With respect to the previous literature, Figure 5clearly shows that international transfers do not represent a negligible share of the US network. Figure 6 proves this point further by decomposing the contribution of domestic and international markets to the total results.Clearly the distribution of both hub dimensions has substantially changed with the introduction of international markets. In spite of that, airports tend to maintain a similar hub profile, i.e. airports that have high level of domestic connectivity also present high levels of international connectivity (e.g. ATL, Chicago-ORD, Dallas/Fort Worth-DFW); while the opposite is also seenin popular tourist destinations(e.g. Las Vegas-LAS, Orlando-MCO).

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[8] A possible explanation for the limited traffic generation might be the lack of critical mass of Atlanta, which population 2012 was just near 450,000 inhabitants, and ranks only as the 11th Combined Statistical Area in the US (See classifications from the Office of Management and Budget).

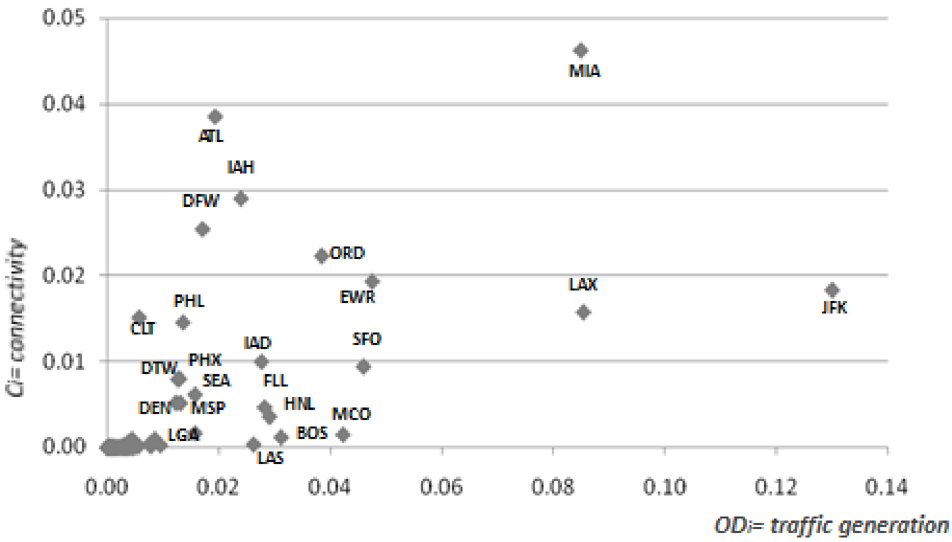


**Figure 5.**Hub characteristics for international markets.
*Source: Own elaboration using MIDT.*

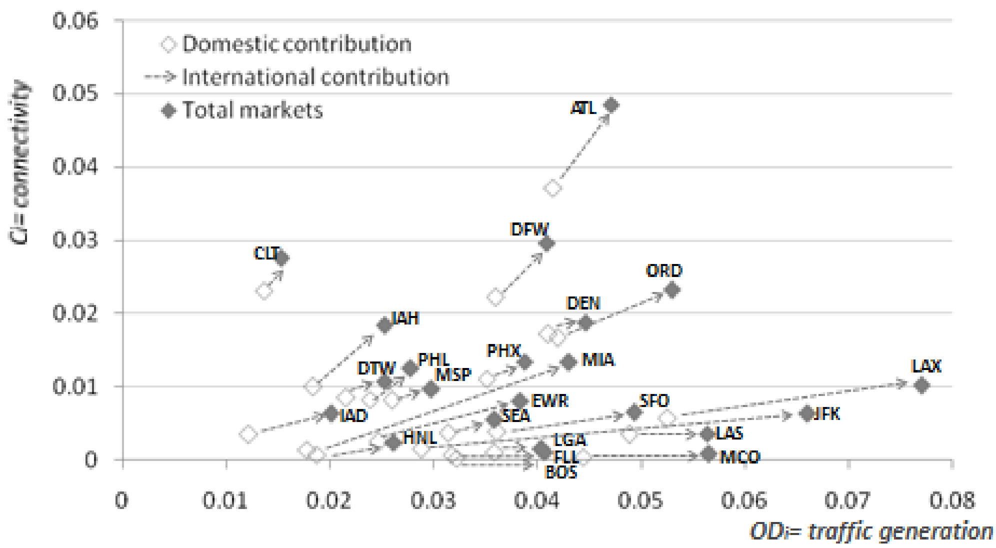


**Figure 6.** International contribution to total markets
*Source: Own elaboration using MIDT.*

An interesting exception to that rule is Miami (MIA). Despite typically ranking second (to JFK) in terms of total international passengers, MIA stands out as the truly international "hub" in the US, with relatively high levels in both dimensions that can be linked to its central location as a gateway to the markets in Latin America and the Caribbean. However, the opposite applies when only domestic markets are considered. MIA becomes a "traffic generator" with very little connectivity, mainly due to its non-central location within the US network. Thisresultreinforces the need to account for all markets when definingan airport's role within a network.

### *4.3 Total markets and airport classification*

Figure 7 indicates the values of connectivity and traffic generation for the complete dataset when all markets are considered. In addition, the equivalence from Table 4 is used in order to represent the different combinations of both dimensions that lead to the same level of the FAA indicator. While the only relevant level is 1%, as the FAA classifies all airports above that threshold as "large hubs", additional levels (up to 6%) are given in order to improve comparability. In this regard, it is clearly seen that airports with similar enplanement shares (e.g. CLT, MIA, and JFK; or DFW and LAX) present radically different hub profiles. Thus, we agree with Rodríguez-Déniz et al. (2013) in concluding that, by aggregating both hub dimensions into a single indicator, the simplicity of the FAA method comes at the cost of discriminatory power. We admit that, given the delicate objective of the classification – allocating AIP funds –, simplicity and transparency are necessary qualities of the chosen method. However, we aim to propose an alternative method that meets these two basic criteria, but that is also sensitive to the diverse roles played by the large airports in the US network, which might have different infrastructure development and funding needs.

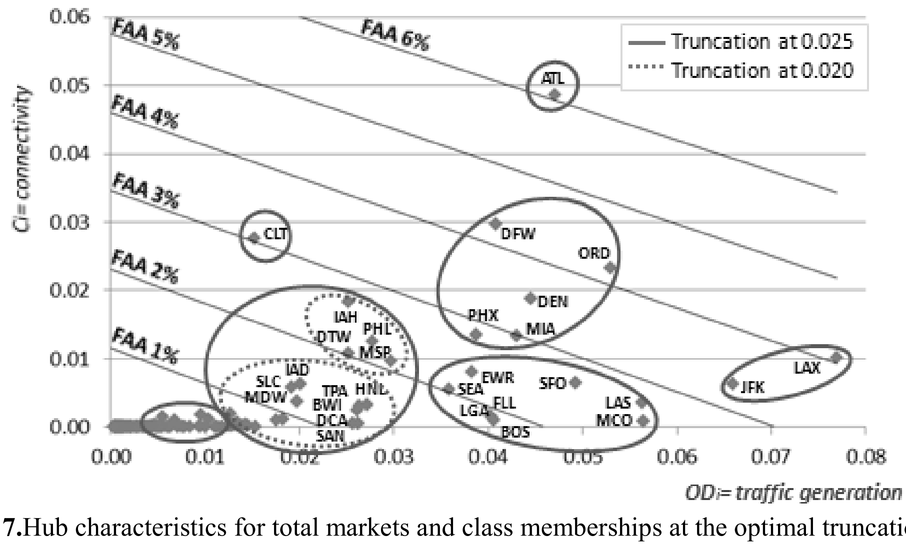


**Figure 7.**Hub characteristics for total markets and class memberships at the optimal truncation level
*Source: Own elaboration using MIDT.*

Ourclassification method is expressed as a set of arbitrarily defined thresholds[9] for connectivity and traffic generation that can be obtained in different ways (including even direct observation of Figure 7). However, we employ AHC as it is useful to reveal hidden structures in the data. The resultingdendrogram and the optimal truncation level are shown in Appendix A. Further exploration of the dendrogram at a lower level of aggregation reveals an inside partition within cluster 6, which becomes relevant to define the airport categories. The actual groups are also shown in Figure 6 and descriptive statistics are provided in Table 6.

While there are many different ways to interpret this partitioning, we found that below 1% connectivity there are three well-defined groups of "traffic generators" differentiated by the size of their *od* contributions. "Hubs" (i.e., strong in both dimensions) are located above that threshold, again differentiated by traffic generation. Thus, we propose to use the connectivity dimension to define the airport type and traffic generation as a size qualifier. An example of one of the many classification systems that can be defined in this way is provided in Table 7, with three size tiers (Tier 1: between 1-3% $OD_i$;Tier 2: between 3-6% $OD_i$;and Tier 3: more than 6% $OD_i$) as suggested by Figure 7. The system is flexible to accommodate "hypothetical" airport categories (such as Tier 3 hubs) or further disaggregation in airport types, such as "superhubs", to label those airports with supra-normal levels of connectivity (ATL).

**Table 6.**Class memberships at the optimal truncation level

| ***Class*** | 1 | 2 | 3 | 4 | 5 | 6a | 6b | | 7 |
|---|---|---|---|---|---|---|---|---|---|
| ***Objects*** | 1 | 5 | 2 | 1 | 8 | 4 | 22 | | 95 |
| | ATL | DFW | LAX | CLT | LAS | IAH | DCA | RSW | |
| | | ORD | JFK | | SFO | PHL | BWI | MCI | |
| | | DEN | | | MCO | MSP | IAD | OAK | Rest of medium and small hubs |
| | | MIA | | | EWR | DTW | HNL | BNA | |
| | | PHX | | | SEA | | SLC | SNA | |
| | | | | | FLL | | TPA | AUS | |
| | | | | | LGA | | MDW | MCY | |
| | | | | | BOS | | SAN | RDU | |
| | | | | | | | PDX | SMF | |
| | | | | | | | SLT | SAT | |
| | | | | | | | HOU | SJC | |
| ***Centroid*** | ATL | DEN | LAX | CLT | LGA | | MDW | | ALB |
| ***Average OD*** | 0.047 | 0.044 | 0.072 | 0.015 | 0.045 | | 0.019 | | 0.004 |
| ***Average C*** | 0.049 | 0.020 | 0.008 | 0.028 | 0.004 | | 0.003 | | 0.000 |

*Source: Own elaboration*

**Table 7.**Example of alternative criteria for regulatory airport classification

| ***Airport type*** | ***Connectivity*** | ***Traffic generation*** | | | |
|---|---|---|---|---|---|
| | | ***<1%*** | ***1-3%*** | ***3-6%*** | ***>6%*** |
| ***Traffic Generators*** | <1% | Non-hub | Tier 1 | Tier 2 | Tier 3 |
| ***Hubs*** | >1% | - | Tier 1 | Tier 2 | Tier 3 |
| ***"Superhubs"*** | >3% | - | Tier 1 | Tier 2 | Tier 3 |

*Source: Own elaboration*

[9]They are at least as arbitrarily defined as the FAA values from Table 1.

The transparency of this method is rooted on the straightforward nature of both indicators, which are easy to define, calculate, and interpret. The loss in simplicity (as now two dimensions are used) is compensated by a better characterization of the roles played by large US airports.

The main application of this bi-dimensional classification is to serve as a more complete typology of primary US airports with the objective to optimize the allocation of AIP funds. It is then the regulators' task to decide how much AIP "entitlement" per passenger would be assigned to each airport category, as well as defining a set of numeric weightings for the NPS formula that properly rank the airports' AIP submissions. The rationale for this differentiated treatment is that large airports with different "hubbing" profiles can be expected to have different capital needs, with "traffic generators" placing emphasis on accessibility and integration with ground transport modes, while "hubs" will also focus on, for example, coordination of arrival and departure waves or the optimization of gate-to-gate connecting times. The crucial role of hubs in the propagation of delays through the US network is another point in favour of a differentiated treatment, especially considering that this is one of the AIP's declared priorities. Finally, note that the definition of our connectivity indicator is partially linked to the concept of "node criticality", as it directly indicates the proportion of system-wide passengers (on top of the relevant *od* ones) that would be affected by any kind of node failure, i.e. airport closures related to weather conditions, terrorist threats, industrial actions, or just excessive congestion.[10]Improving the robustness and resilience of the US airport network, as a high-level objective of the transport regulator, also provides justification to improve the funding allocation system with the proposed method.

It is also important to stress that the differentiated treatment with respect to hubbing characteristics does not directly imply the existence of "winners" of "losers" from the proposed system. In fact, all airports could be winners if they are given higher weightings for the AIP projects that match their hubbing profile. It is only the definition of size tiers (completely at the discretion of the regulator) that is going to generate "winners" and "losers". We predict that, under our arbitrary classification from Table 7, those airports with

[10] In this regard, however, our indicator presents the limitation that it is exclusively based on traffic data and does not take into consideration the topological properties of the US airport network. The way in which airports are connected to each other can affect how critical the observed connections actually are, particularly in regards to the alternative routings available to the disrupted passengers. Other authors have proposed indexes such as "adjusted essential betweeneess" (Malighetti et al., 2009) that combine traffic data and network topology, which would, in principle, provide a more complete characterization of airport criticality.

higher levels of traffic generation (Tiers 2 and 3) would receive larger weightings than the airports in Tier 1 (Clusters 6a and 6b in Table 6). These financial implications should be taken into account when implementing this method. In spite of that, the threat that AIP investment may end up concentrated in just a few large hubs is mitigated by the fact that the "airport size and role" is just one of the factors within the AIP formula to assign funding priorities, while other factors linked to the actual nature of the project play a larger role. Finally, it is also worth clarifying that our classification only affects the airports defined as "large hubs" by the FAA and hence, small non-hub airports, with negligible levels of connectivity, are not treated differently than before.

## 5. SUMMARY AND CONCLUSIONS

Within a context of financial constraints for the US FAA, this paper focuses on the enplanement-based airport classification method used to allocate funds for capacity developments under the Airport Improvement Program. Previous papers have already addressed the limitations of the FAA method and proposed alternative approaches that explicitly separate traffic generation and connectivity as the two dimensions of "hubbing" activity. However, these studies are biased by the lack of detailed data on international markets, which distorts the results for the largest airports. Using an MIDT dataset on domestic and international markets served by US airports during the first quarter of 2013; this paper provided a picture of the pitfalls of the FAA method by assessing the impact of international connectivity in characterising the airports' hubbing profiles. Secondly, we specified an alternative set of criteria for hub classification, for which hierarchical clustering techniques were used.

Results indicate that international markets contribute 16% in terms of traffic generation and 29% of all connecting passengers in the US airport network. Regarding the individual airports, even though large international gateways in the US are well identified, the data shows that their hubbing profiles for the international markets vary widely. For example, while Atlanta stands out as an international waypoint (with large connectivity and reduced traffic generation), New York's JFK presents the opposite profile, with a vast majority of its international passengers originating or terminating at the airport. These significant differences suggest that a more careful characterisation of international gateways is necessary.The same conclusion is obtained when domestic and international markets are combined.It becomes clear that the uni-dimensional FAA method trades off discriminatory power by simplicity and does not accurately characterise the different roles played by large airports in the US. The hierarchical clustering reveals seven distinct aggrupations in the dataset.Around the edges of these clusters we devise a simple method for hub classification in the context of the NPIAS that is flexible and readily applicable.

On one hand, this new typology of primary US airports can help to optimize AIP funding by allowing for further differentiation in the FAA allocation criteria. The rationale for this differentiated treatment is that traffic generators and hubs can be expected to have different capital needs. In addition, the potential benefits of AIP projects, especially with regard to delay reduction and network resilience, are also sensitive to the airports' "hubbing" profiles. Despite these benefits, it is also worth noting that the FAA could face difficulties in implementing the proposed approach. Firstly, any change in the airport funding allocation procedures can raise political rows between the perceived "losers" and "winners" of the new system. Secondly, whilst MIDT data might be useful for research purposes and for showing the usefulness and applicability of the proposed methodology, for transparency and accountability reasons governmental funding should rely on primary data provided by airport and airline companies. Therefore an official protocol for data reporting should also be implemented.

Finally, note that this paper is limited by the temporal scope of our MIDT dataset, which covers only one quarter, and the absence of multi-stop connectivity, which can provide insights for studying super-long-haul travel. Further research on this topic could explore the contribution of network airlines and LCCs to airport "hubbing", expand the temporal dimension of the dataset, or the scope of analysis (e.g., other countries or the worldwide network). In particular, a time-series analysis of "hubbing" activity in a developing airport network would allow us to analyse the dynamics of network formation and the geo-economic factors that influence the roles assumed by the respective airports.

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**APPENDIX A.** Airport dendrogram (truncation = 0.0025)